International Journal of Mechanical and Production Engineering Research and Development (IJMPERD)
ISSN (P): 2249–6890; ISSN (E): 2249–8001
Vol. 9, Issue 5, Oct 2019, 319–332

NEURAL NETWORK MODEL SELECTION FOR DYNAMIC STRAIN MEASUREMENT USING FREQUENCY-DOMAIN PARAMETERS OF FIBER OPTIC SENSOR

A. S. WALI & AMIT TYAGI

Department of Mechanical Engineering, IIT (B. H. U), Varanasi, India

ABSTRACT

The present study is aimed to develop a smart strain prediction model using fibre optic sensors and neural network. Frequency domain optical parameters are obtained experimentally using a cantilever beam structure, under dynamic loading conditions. Four variations with external damage are used to study strain variations on healthy, single damage and multiple damage beam structures. The strain values were correlated to the set of phase difference, change in real part and amplitude by using feed-forward back propagation neural network approach. The strain values using optical parameters were verified with analytical strain measurement. As the signals always get affected due to the presence of noise, this drawback is eliminated using a well trained neural network model. The neural network model provides a better and advanced methodology for strain prediction compared to the conventional analytical solution.

KEYWORDS: Optical parameters, Neural network, Finite Element Analysis & Strain

Received: Jul 01, 2019; **Accepted:** Jul 21, 2019; **Published:** Sep 12, 2019; **Paper Id.:** IJMPERDOCT201927

Original Article

1. INTRODUCTION

Structural health monitoring, or SHM for short, is the process of establishing some knowledge of the current condition of a structure. The ultimate goal is to determine the existence, location, and degree of damage in a structure if damage occurs. Structural health monitoring has attracted much attention in both research and development in recent years. The process of implementing a damage detection and characterization strategy for engineering structures is referred to as Structural Health Monitoring (SHM). Here the damage is defined as changes to the material and geometric properties of a structural system, including changes to the boundary conditions and system connectivity, which adversely affect the system's performance. The SHM process involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of system health. In general, a typical SHM system includes three major components: a sensor system, a data processing system, and a health evaluation system. The sensors utilized in SHM are required to monitor not only the structural status, for example, stress, strain, displacement, acceleration, etc. but also influential environmental parameters, such as wind speed, temperature and the quality of its foundation. Most of the conventional sensors used in the above-mentioned health monitoring applications are based on the transmission of electric signals.

In recent past, optical fibers have been widely deployed in telecommunication industries owing to their special performance as the best light guidance. Besides, with the development of optoelectronic technology, optical

fibers have been intensively investigated at various sensor fields owing to their unique characteristics such as multiplexing, high flexibility, remote sensing, low fabrication cost, immunity against electric and magnetic fields and many more. Some research had shown the use of mechanical cables for structural health monitoring. The study proposed that a fiber optic system can be used to deduct wire breakage in mechanical cables under working conditions [1]. Studies with the advancement in areas of sensing system signal processing, communication, and data mining technologies, give new area for inspection and monitoring. Health monitoring of structures like bridges had been carried out using fiber optic sensors [2]. A different study in the area of structural health monitoring is observed by using embedded fiber optic sensors for deformation measurement under various loading conditions [3–4]. Some recent studies show successful use of fiber optic sensor on aerospace structures. The test was performed under real-time dynamic loading using FBG (fiber Bragg grating) sensors [5]. Recent research investigates the feasibility of using FBG sensors for health conditioning measurement by monitoring the strain of different parts of the structure under railway and highway loads [6]. An important advancement in the area of optical fiber sensors provides a positive alternative with the advancement in structural health monitoring. Recent investigation successfully employed Mach-Zehnder interferometric sensors to measure the dynamic strain. A vibrating cantilever beam is taken as a host material and the results were compared with conventional strain gauge measurement [7]. Successful assessment of low strain measurement was performed for structural health monitoring using a fiber optic sensor [8]. Many researchers had carried out finite element analysis for strain verification on different civil structures. A similar analysis is performed on a cantilever beam and results were compared with experimental analysis [9]. Recent comparative study for output convergence is done using linear and quadratic element [10]. A neural network is a machine learning process which can be successfully used in the area of structural health monitoring. An artificial neural network is an interconnected assemblage of artificial neurons that uses a mathematical or computational model of theorized mind and brain activity, attempting to parallel and simulate the powerful capabilities for knowledge acquisition recall, synthesis, and problem-solving. The investigation provides a damage assessment method using neural network analysis. The network was trained and tested for damage and undamaged state where strain and displacement are used as network parameters [11]. FBG sensors are used for strain measurement thus measuring the reliability of the civil structures. In a study, FEA strain data is successfully used in the neural network to predict the defect present in structure [12]. Recent research shows the use of displacement and strain as input parameters for the back propagation neural network to assist the location of damage in a cantilever beam [13]. Performance of a neural network is based on the number of neurons present in the hidden layer and the number of hidden layers in network architecture. Concepts are developed to set selection criteria for the number of neurons in a network [14]. Over and under fitting is an important criterion which plays an important role in developing a neural network model [15]. Some study uses feed forward back propagation neural network model for strain approximation using airspeed and angle of attack as input parameters in the aerodynamic analysis [16].

2. METHODOLOGY

In past years a lot of research had been carried out to study the behavior of different materials. Various parameters like modulus of elasticity, strain, stress and many more contributed to studying the characteristics of a material system. The strain is one of the basic parameters which have an important role in understanding material behavior. Many researchers had contributed to studying strain and its variation under different conditions. Methodologies like strain gauge measurement, tensile test, extensometer, and others help study the strain. These conventional methods come with some disadvantages like a restriction of sample dimension in the tensile test, extensometers cannot be applied in case of multiple strain deduction, and strain gauges can only be used with high skill and training with localized strain measurement. Advancement in the area

of smart material opens a new dimension in measuring the material parameters using smart technology. Development of materials like lead zirconate titanate (PZT), and technology like piezo-impedance transducer are globally accepted smart measurement methods for structural health monitoring. Another advantage of using these smart methods is that these methods are nondestructive. A major disadvantage of using this piezo technology is that their measurements get affected in the presence of electric and magnetic fields. Advancement in fiber optic technology overcomes the disadvantages of conventional strain measurement systems.

Advantage of using fiber optic sensors (FOS) is that it overcomes the disadvantage of getting affected in electromagnetic fields. Add on advantage with fiber optic sensors are multiplexing, high flexibility and low propagation loss with accurate measurement. Many researchers had used the optical signals for deduction of strain in a material system. In this work, an experimental investigation of using fiber optic as a sensor is carried out. The advancement is made by using a neural network for strain prediction using various optical parameters like phase, real part, imaginary part, amplitude, magnitude. The neural network is a part of artificial intelligence which works on the back propagation method. Back propagation methodology allows the network to adjust its weight and bias to approximate required output. In present work, a single layer perceptron model is used to successfully predict the strain values under different dynamic loads.

3. FIBER OPTIC SENSORS (STRAIN AND PHASE CHANGE RELATION)

A basic of working of optical strain sensor is based on strain-induced phase shift that occurs in light signal traveling in an optical fiber. Sirkis and Haslach showed that only an axial component of strain in a surface-mounted optical fiber affect the index of refraction [17]. Elemental analysis is performed to obtain gives the relation of change in phase of fiber with variation in the index of refraction along its length. For a small elemental segmental length (Δs) the index of refraction is approximated as a constant equal to n(s). Phase change relation exists as shown in equation 1.

$$\Delta\emptyset = \frac{2\pi}{\lambda} n(s)(1+\epsilon_n)\Delta s \tag{1}$$

Limiting the value as $\Delta \rightarrow 0$ we get

$$\frac{d\emptyset}{ds} = \frac{2\pi}{\lambda} n(s)(1+\epsilon_n) \tag{2}$$

On integrating equation 2 along the length of the fiber

$$\emptyset = \frac{2\pi}{\lambda}\int_0^L n(s)(1+\epsilon_n)\,ds \tag{3}$$

Equation 3 shows that the phase is an increasing function with L. Index of refraction in a surface-mounted fiber based on the function of ϵ_n up to first order as

$$N(s) = n_0(1-c\epsilon_n) \tag{4}$$

where n_0 index of refraction under the unstrained condition and c is defined as

$$c = \frac{n_0^2}{2}\{p_{12} - \nu_f(p_{11} + p_{12})\} \tag{5}$$

where p_{ij} is pockel's constant and v_f is the Poisson ratio. Now assuming $\beta = 2\pi n_0/\lambda$ and ignoring higher-order terms we get

$$\emptyset = \beta\int_0^L (1-c\epsilon_n)(1+\epsilon_n)\,ds = \beta L + \beta(1-c)\int_0^L \epsilon_n ds \tag{6}$$

Butter and Hocker [18] strain equation is obtained for the strained and unstrained condition as shown in equation 7.

$$\Delta\emptyset = \beta(1-c)\int_0^L \epsilon_n ds = \beta(1-c)\,\epsilon_{avg.} \quad (7)$$

where $\epsilon_{avg.}$the average strain isdeveloped an optical fiber. To develop a sensor design using this phase change property of optical fiber we have to express the sensing and reference path as a function of optical parameters. As derived by Haslach [17], sensing and reference path can be expressed in the x-y coordinate system and surface strain variation can be obtained in the x-y coordinate system is shown in equation 8.

$$\Delta\emptyset = \beta(1-c)\int_0^L \epsilon_n ds$$

$$= \beta(1-c)\int_0^L \frac{(\epsilon_{xx}x'^2 + \epsilon_{yy}y'^2 + \gamma_{xy}x'y')}{(x'^2+y'^2)} . \sqrt{x'^2 + y'^2}dt \quad (8)$$

For simplifying above integral we assume

$$k_1 = \int_0^L \frac{x'^2}{\sqrt{x'^2+y'^2}}dt \quad , \; k_2 = \int_0^L \frac{y'^2}{\sqrt{x'^2+y'^2}}dt \; , \; k_3 = \int_0^L \frac{x'y'}{\sqrt{x'^2+y'^2}}dt$$

Now equation 8 simplifies as

$$\Delta\emptyset = \beta(1-c)\,[\epsilon_{xx}k_1 + \epsilon_{yy}k_2 + \gamma_{xy}k_3] \quad (9)$$

Applying co-ordinate conditions at $y'=0$, $k_2 = k_3 = 0$, thus above equation 9 became

$$\Delta\emptyset = \beta(1-c)\,[\epsilon_{xx}k_1] \quad (10)$$

From equation 10 it is clear that change in phase is directly related to the change in the axial strain for a surface-mounted fiber optic sensor.

Effectiveness of a transmission system highly depends on the noise factor. Presence of noise defines the quality of the output signal on which the system performance depends. Noise is more significant parameter if high-frequency source like laser is involved in the analysis. There exist different types of noise in signal analysis. The occurrence of noise initially depends on the circuitry of the source, which is known as internal noise. In laser output signals mode partition noise is another for which occurs due to the Fresnel reflection phenomenon. As the laser output signal has a specific wavelength which satisfies both gain and phase condition between two reflecting regions in laser.

Speckle patterns are defined by redistribution of power over the cross-section of the optical fiber core. Because of the presence of variation in the wavelength components in the optical signal, it undergoes different phase changes with respect to time. The speckle pattern is a time-dependent quantity which varies with respect to time. Fluctuation in output signal occurs due to this variation with time and the non-uniform power detection capability of the photo-detector over its entire cross-section. This noise type of noise is called speckle noise [19].

Calculation of strain using surface-mounted optical sensor given in equation 10 provide analysis only in static loading condition. Under dynamic loading, the results of the analytical analysis may provide diverging results. Moreover, the noise in the signals also contributes to the variation of results. Different methods exist to remove the noise data using filters and other software. But the same signals can be successfully used to determine strain values using neural network technology. Neural network technology is cheaper and practically applicable to different problems which require data mining.

4. EXPERIMENTAL SETUP

An aluminum beam of dimension 180*24*6 mm^3 is selected as experimental samples for analysis. Gauge length is selected at 60 mm in the middle of the beam length. Fiber optic cable and is bonded at the top surface at the middle of the beam. Notches are made at four different locations of the beam within the gauge length. Variations in the location of the notches are made at 75 mm, 90 mm, and 105 mm from the fixed end. A digital storage oscilloscope of frequency range 1 kHz-2000 kHz is used for storing the signal data. A helium-neon laser of wavelength 1556nm is used for generating the laser beam. The refractive index of the optical fiber used for sensing is 1.45. An optic-electric converter is used for converting the output optical signal from the sample to an electric signal to be stored in the oscilloscope. A small motor of unbalance mass of 2 gram is mounted at the free end for dynamic loading. A loading pan is used to load the samples with different loads to provide variation in applied amplitude. Symbolic representations of different types of samples used in the analysis are shown in table 1.

Table 1: Samples used in the Study

Types of Samples used in the Analysis	Symbols
Sample without notch	A
Sample with the single notch at the center within gauge length (notch at 90 mm.)	B
Sample with double notch within gauge length (notch at 75 mm. and 105 mm.)	C
Sample with three-notch within gauge length (notch at 75 mm, 90 mm, 105mm.)	D

4.1 ANOVA Analysis

Analysis of experimental data is performed using a statically approach ANOVA. Time-domain signals are converted into a frequency domain signal using fast Fourier transformation. Analysis of variance is performed using different signal parameters under the Tukey test with a significant value of 0.05. ANOVA test for the real part, amplitude, and phase show that for the sample size of 1000 sample inter quartile range doesn't show much difference in all the different sample categories moreover median values also show a significant difference. Analysis of imaginary part and magnitude show that for the sample size of 1000 sample inter quartile range doesn't show much difference in all the different sample categories moreover median values also doesn't show any significant difference. The test result is summarized in table 2. Thus from this test approach, we can say that significant variation corresponding to external host occurs only in real part, amplitude and phase of the signal.

Table 2: ANOVA Analysis under Different Loading

Load(N)	Sample Type	Real Part	Imaginary Part	Magnitude	Amplitude	Phase
2N,4N,6N,8N,10N	Sample A- Sample B	1	0	0	1	1
	Sample A-Sample C	1	0	0	1	1
	Sample A-Sample D	1	0	0	1	1

5. FINITE ELEMENT ANALYSIS

Finite element analysis is one of the most accurate and precise tools used by different researchers and analysts. Four different cantilever beam models (sample A, B, C, D) were generated using 20 node beam 189 elements with dimension as 24*6*180 mm^3. A cantilever beam is modeled for aluminum beam as linear, elastic and isotropic. Properties of material such as modulus of elasticity equal to 70GPa and Poisson ratio equal to 0.33 are used to develop a smart mesh model. Boundary condition applied in FEA analysis is one end of the beam with all degree of freedom equal to 0 and

another end of the beam free for loading. For applying Dynamic loading at the free end of the beam a loading function is defined in function editor as given in equation number 11.

$$LoadingFunction = A * \sin(\frac{\pi}{2} * \{TIME\}) \tag{11}$$

After defining the function it is saved to be used for loading. A is the amplitude of the loading function defined as in equation 12.

$$A = m\_(0\ )\ e\omega\hat{}2 \tag{12}$$

Where m_0 is mass of unbalanced mass equal to 0.002 kg, e is the eccentric distance equal to 0.02 m and ω is the angular velocity equal to146radian/ second. The saved function is selected for applying dynamic ramped loading time step size equal to 1. Time at the end of the load step is selected as 20. An additional point load is applied at the middle node of the free end of the beam to obtain variation in amplitude of dynamic loading. After the solution, the values of axial von-misses strains values at the middle node on the top surface under different loading conditions are obtained.

6. NEURAL NETWORK ANALYSIS

Recent advancement in structural health monitoring includes active use of neural network technology for analysis. A neural network is incorporated with small processing units known as neurons. ANN includes three basic layers input, hidden and output layer. The network takes variable parameters as input in input layer then processing is done and it is transferred to the hidden layer. Hidden layer contains some activation function which explores the weights and bias of variable for prediction of target values. The output layer is designed to store predicted value with some error estimation. The back propagation algorithm is applied in the neural network. The main disadvantage of using back propagation is slow convergence and over fitting. To overcome the problem of convergence two algorithms namely Leven berg-Marquardt and Bayesian regularization are tested which will be discussed in section 7.1. To counter over fitting of data set cross-validation is performed. In this study selection of the algorithm is based on the regression analysis and mean square error which is performed sample A under different loading conditions.

The signal output of the fiber optic signal is generated from the surface-mounted optical sensor. Thousand data points are obtained per sample under specific loading. Applying fast Fourier transform different optical parameters like the real part, imaginary part, amplitude, magnitude, and phase are generated. Comparative ANOVA study in table 2 show, that signature values of the real part, amplitude and phase give a significant difference. These three optical parameters are used as input to the designed neural network to predict dynamic strain values on the host material. A tansig activation function is used in the network has a range 0 to 1. The function is shown in equation number 19. Normalization of input data is done for obtaining data in range with function range value.

$$f(z) = \frac{1}{1-e^{-z}} \tag{13}$$

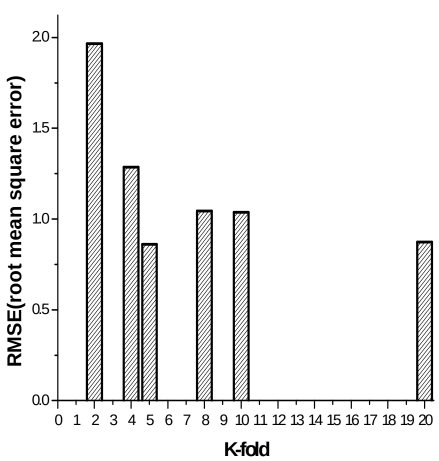
6.1 Selection of Test and Train Data

Different cross-validation methods are present which can be used in the machine learning process. Cross-validation is a method of estimating expected prediction error thus helping in selecting the best fit model for a required problem. It also encounters the problem of over fitting of the model. There exist various cross-validation models like the holdout method, k-fold cross-validation, and leave one out cross-validation and bootstrap method. In hold out method two

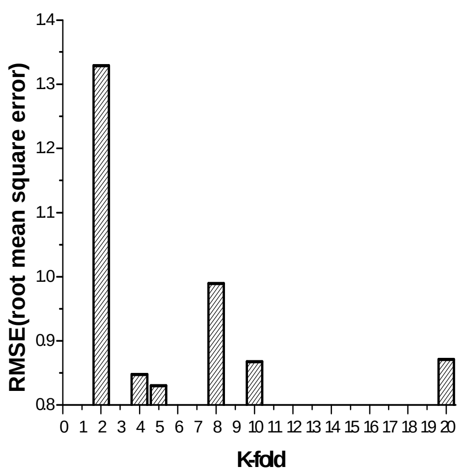
subsets are formed, one part of the sample is considered for training and another part is tested. A drawback of this model is its dependency on data selection. Output performance is directly affected by changing the training and holdout subsets. In k-fold cross-validation, the sample is divided into k subsets. One subset is considered for validation and rest subsets are taken for training. In further analysis different subset is taken under validation and rest subset data is considered for training. This process continues until all subsets are analyzed sequentially by the model. Advantage of using this method is that each subset forms sample for training and validation. This data division reduces the selection bias that is present in hold out cross-validation.

Leave one out cross-validation is a more generalized form of k-fold method. In this method, each data is considered as the validation set and rest data is taken for training. Similar k-fold sequential analysis is performed to calculate the error for each validation set. The main drawback of this method is that it is expensive and time of computation is high. Bootstrap is another known method for cross-validation. In this method, random data is selected. Selection of the model is based on the refitting and error estimation of model performance. This process also carries high computation cost and time.

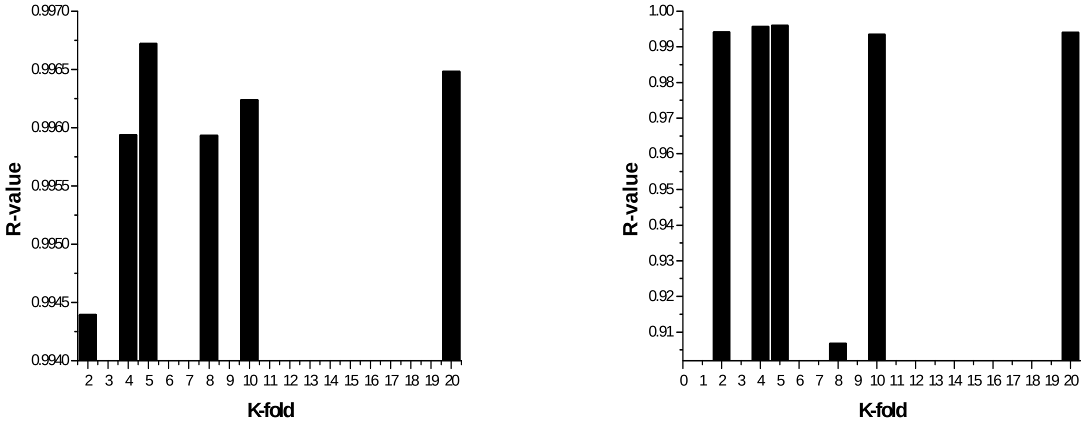
Data of 4000 data corresponding to different samples (A, B, C, D) under specific loading is obtained. Data contains optical parameters like real part, phase change, amplitude, and target strain values. In the present study k-fold method (k = 2, 4, 5, 8, 10, 20) is analyzed for error validation of neural network model. As the sample size is 4000, therefore, several k-folds are selected to give even distribution of data in respective subsets. Comparison of Leven berg-Marquardt (LM) and Bayesian Regularization (BR) is carried to select best artificial neural network model for strain approximation under dynamic loading. Single-layer perceptron model with 10 neurons in the hidden layer is used for model validation. The selection criterion for the best neural network model is based on the minimum root mean square error (RMSE) and maximum regression value (R-value) of the model. figure.1(a) shows a comparison of models based on LM and BR algorithm, where minimum root mean square error is obtained at a k-fold value of 5. Similar results were obtained related to regression value histogram shown in figure1(b), in which maximum regression value is obtained at k-fold equal to 5. A k-fold value equal to 5 indicates that the best neural network model is obtained if 20% of data is used for testing subset and rest is used in the training subset.



(a) Root Mean Square Error using LM Algorithm.



(b) Root Mean Square Error using BR Algorithm.



(c) Regression Analysis using LM Algorithm. **(d) Regression Analysis using BR Algorithm.**

Figure 1: Results of k-Fold Analysis at Different k Values.

6.2 Neural Network Architecture

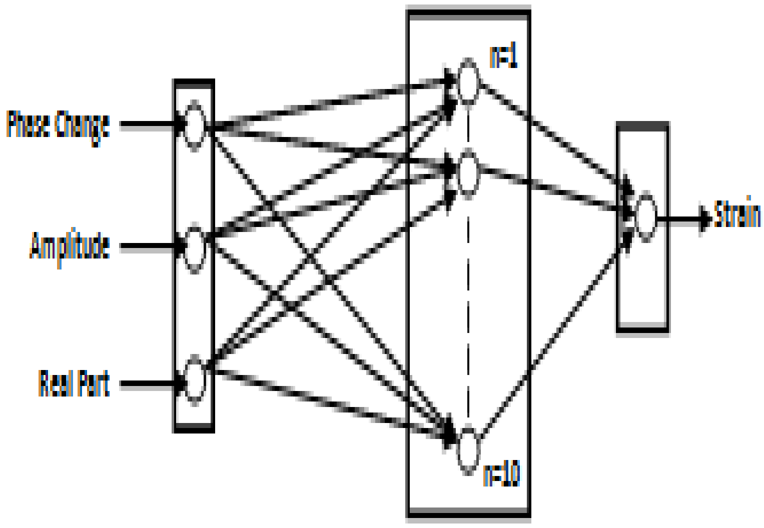


Figure 2: Schematic Representation of the Neural Network Model.

Table 3: Parameters of ANN Perceptron Architecture used in the Study

The Number of Neurons of Different Layers	**Input : 3, Hidden : 10, Output : 1**
Initial weight and biases	Random between -1 and 1
Activation function	Tan sigmoid
Learning rule	Backpropagation
Epoch value	1000
Acceptable mean square error	0.001

A back-propagation feed-forward single layer perceptron model is developed. Three optical parameters real part, amplitude, and phase is considered as input data and strain is recorded as an output parameter in ANN design. ANN includes three layers for processing. Input layer takes the input parameters. Following the input, layer comes hidden layer which contains transfer function. Transfer function help to adjust weight and bias of the variable, thus exploring the effect

of predictors upon the target values. The output layer is used for result prediction with error estimation. At the end of process test data is used for analyzing the system accuracy. ANN model used in this study is shown in table 3, and the block diagram of ANN architecture is shown in figure 2.

7. RESULTS AND DISCUSSIONS

Samples based on different notch location are tested for analyzing strain variations. In present work, the cantilever beam structure is considered as a host material for strain determination. Samples have fiber optic cable mounted on the surface for obtaining the change in optical signals at different loadings. Dynamic loading is applied using unbalance rotating mass at the free end of each sample. Weight pan method is applied to obtain a change in amplitude of dynamic loading. Loading sequence includes starting from 2N to 10N with incremental load step of 2N. Amplitude, phase change and real part of the optical signal are used as input data for the designed neural network. Strain values obtained using finite element analysis is set as target values in the neural network perceptron model. The k-fold analysis provides a logical output for the selection of test and train data. Moreover, the k-fold analysis also eliminates the possibility of over fitting and under fitting condition. The Bayesian regularization back propagation algorithm is used in this study for designing the neural network. Testing and training regression values are above the acceptable limit of 90%. Epoch is set to a maximum limit of 1000.

Figure 3 Show the performance plot of the multilayer perceptron model. Performance plot is based on the mean square error of the developed model. It is clear from the figure that the developed model works with high confidence and least error values. Mean square error plots of different data set at various loading show that model well predicts the target values. In fig 3 (a) mean square error for test and train data reduces and became constant after 40 epoch value. For 4N load in figure 3 (b) mean square error reduces initially. But a steep reduction is observed near 50 epochs. A constant value is attained after 200 epoch value. Similarly, in fig 3(c) test and train curve separates near 30 epochs but became constant after 150 epoch value. In figure 3 (d) constant reduction in mean square error curve is obtained which became constant at 60 epochs. Figure 3 (e) shows a steep reduction in mean square error near 200 epochs and curve became constant after 450 epoch value.

Table 4 presents the obtained values of different ANN parameters used in the analysis. Regression values are analyzed for the acceptability of the developed ANN model. From the table, it is clear that all regression values are very close to 1. Values of data comparison by regression analysis prove that the developed ANN model works well within the acceptable range of regression and standard error. Regression value corresponding to 10N, show low range which ultimately increases the error. But still, the values provide a satisfactory condition acceptance. Figure 4 shows the strain comparison of various samples under different dynamic loading. Different sample show variation Strain values for analytical and developed neural network model. It is observed that neural network model prediction are more accurate compared to the analytical solution given by Haslach [17]. Based on the strain analysis following conclusions can be drawn:

- Over and under prediction of strain values are observed using analytical analysis. This random variation occurs due to the incapability of the analytical solution to deal with the dynamic loading. Moreover, random variation may be due to the presence of noise factor as defined in section 3.
- A good agreement in neural network prediction and target value occurs. Advantage of using this model is that it eliminates the effect of noise present in the signal.

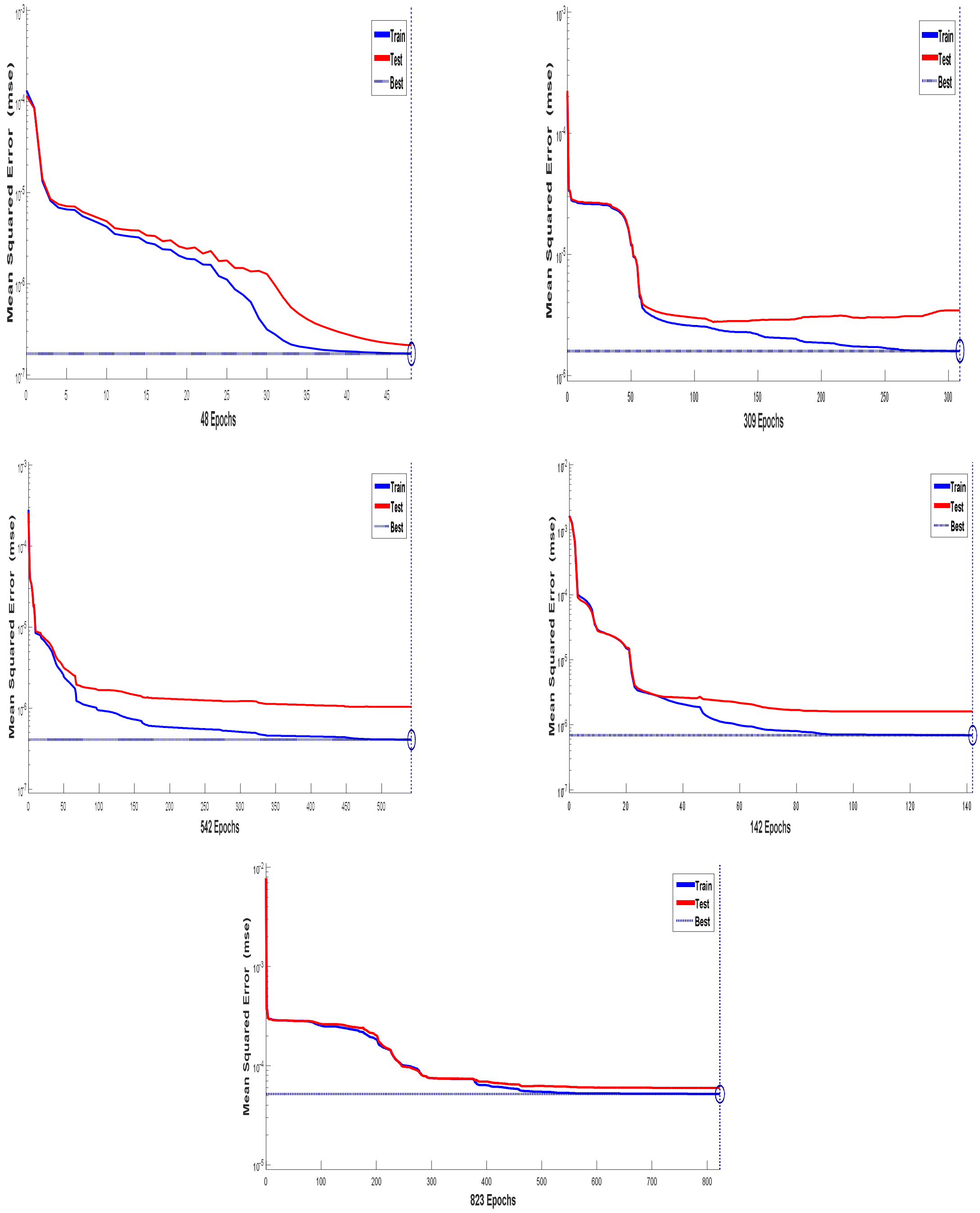


Figure 3: Mean Square Error Plots of Data Set of Different Samples at Different Loadings: (a) 2N, (b) 4N, (c) 6N, (d) 8N, (e) 10N.

Table 4: Performance Effectiveness of Neural Network Model at Different Loads

Load	Training (R-value)	Testing (R-value)	All (R-value)	Epoch	Best Training Performance
2N	0.99349	0.99166	0.99315	48	$1.7129e^{-7}$
4N	0.98398	0.99662	0.98031	309	$1.5927e^{-6}$
6N	0.99828	0.99548	0.99773	542	$4.0987e^{-7}$
8N	0.99835	0.99619	0.99792	142	$6.6898e^{-7}$
10N	0.93753	0.92414	0.92631	823	$5.1957e^{-5}$

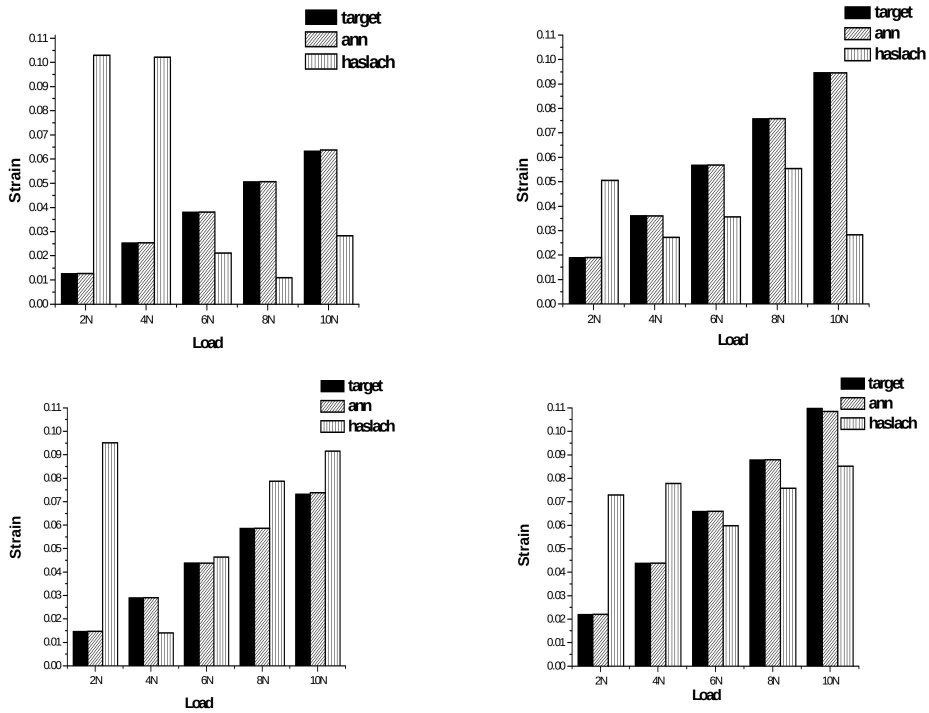


Figure 4: Strain Comparison Plots of Data Set of Different Samples: (a) Sample A, (b) Sample B, (c) Sample C, (d) Sample D

8. CONCLUSIONS

The present study proposes an artificial neural network model to predict the strain value of different samples under dynamic loading. Neural network model uses frequency-domain optical parameters for predicting the structural strain successfully. Cantilever aluminum beam structure is used in this analysis. The first part of the study defines criteria for the selection of a proper neural network model using k-fold analysis. Root mean square error and regression analysis show that the best model is obtained at k- fold value equal to 5. A best neural network model is formed using Bayesian regularization algorithm compared to the Levenberg-Marquardt algorithm. Three basic optical parameters which include the change in phase, amplitude, and real part are used as an input variable for the neural network. Finite element strain values are taken as target values for the network analysis. Figure 3 show means square error plots of different train and test state of the developed model. Obtained plots prove successful and accurate model prediction ability. Target prediction performance parameters are given in table 4. Comparative analysis of strain values is shown in figure 4. The analytical solution developed in the previous study [17] will not be applicable practically under dynamic loading. Moreover, fluctuation in signals occurs because the presence of noise also affects the analytical solution. The problem of over fitting and under fitting of the strain prediction is eliminated using the neural network. The proposed network model provides new insights in improving the prediction accuracy of the mechanical strain of cantilever structure under dynamic loading.

REFERENCES

1. *Daniel Cortázar, Hilda A. Larraondo, Patricio A. A. Laura, and Daniel R. Avalos. A Low-Cost Fiber-Optic System for Monitoring the State of Structural Health of a Mechanical Cable. Ocean Engng, Vol. 23, No. 2, Pp.193–199, 1996. Copyright 1995 Elsevier Science Ltd. Printed In Great Britain. All Rights Reserved 0029–8018/96.*
2. *Ibrahim, R. H. Properties of Jovian Radio Bursts at Frequency 20.1 Mhz.*

3. J. M. Ko and Y. Q. Ni. Technology developments in structural health monitoring of large-scale bridges. Engineering Structures 27 (2005) 1715–1725. 2005 Elsevier Ltd.
4. SherifYehia, TahaLandolsi, Mohamed Hassan and Mohammed Hallal. Monitoring of strain induced by heat of hydration, cyclic and dynamic loads in concrete structures using fiber-optic sensors. Measurement 52 (2014) 33–46. 2014 Elsevier Ltd.
5. Jaggi, S. H. I. K. H. A., & Yadav, A. S. (2014). Distribution of ABO and Rh (D) Allele Frequency among Four Endogamous Populations of Haryana. International Journal of Research in Applied, Natural and Social Sciences, 2(2), 77–80.
6. Kara Peters, Philip Pattis, John Botsis, Philippe Giaccari. Experimental verification of response of embedded optical fiber Bragg grating sensors in non-homogeneous strain fields. Optics and Lasers in Engineering 33 (2000) 107}119.2000 Elsevier Science Ltd.
7. A. Panopoulou, T. Loutas, D. Roulias, S. Fransen, V. Kostopoulos. Dynamic fiber Bragg gratings based health monitoring system of composite aerospace structures. Acta Astronautica 69 (2011) 445–457. 2011 Elsevier Ltd.
8. Khesbak, M. S., Khaleel, I. M., & Ali, R. M. (2015). Enhanced Ac-To-Ac Frequency Changer Based on Multi-Phase Smart Comparative Commutation. Internationa L Journal of Scientific & Engineering Research, 6, 31–44.
9. T. H. T. Chan, L. Yu, H. Y. Tam, Y. Q. Ni, S. Y. Lin, W. H. Chung, and L. K. Cheng. Fiber Bragg grating sensors for structural health monitoring of Tsing Ma bridge: Background and experimental observation. Engineering Structures 28 (2006) 648–659. 2005 Elsevier Ltd.
10. Shiuh-Chuan Her, Chih-Min Yang. Dynamic Strain Measured by Mach-Zehnder Interferometric.Optical Fiber Sensors. Sensors 2012, 12, 3314–3326; doi: 10. 3390/s120303314. ISSN 1424–8220.
11. Chakraborty, S., & Rahman, I. An Estimation to Speaking Frequency in Video Streaming.
12. Bradley Regez, Mohammad Sayeh, Ajay Mahajan, Fernando Figueroa. A novel fiber optics based method to measure very low strains in large scale infrastructures. Measurement 42 (2009) 183–188. 2008 Elsevier Ltd.
13. Erklig A, and Kutak M. A, "Experimental finite element approach for stress analysis", Hindawi Publication Corporation, Journal of Engineering, Vol. 2014, article id 643051.
14. Osuji S. O and Adegbemileke S. A, “Modelling convergence of finite element analysis of cantilever beam", Journal of the Nigerian Association of mathematical physics", Vol. 30, 2015.
15. Maity, D., and Saha, A. (2004), “Damage assessment in structure from changes in static parameter using neural networks”, Publisher Springer India, Issue 3, Vol. 29.
16. Gupta, N., Kamath, G. M., Sundaram, R., Rao, M. S., and Kumar, P. S.(2004), “Structural Health Monitoring of Composite Structures Using Neural Networks”, Proceedings of INCCOM-3 Third ISAMPE National Conference on Composites. Research and Development Establishment (Engrs), Pune.
17. Maity, D., and SAHA, A. (2004), “Damage assessment in structure from changes in static parameter using neural networks”, Sadhana Vol. 29, Part 3, pp. 315–327.
18. Karsoliya, S. (2012), “Approximating Number of Hidden layer neurons in Multiple Hidden Layer BPNN Architecture”, International Journal of Engineering Trends and Technology, Volume 3, Issue 6, 714–717.
19. Panchal, F. S., and Panchal, M.(2014), “Review on Methods of Selecting Number of Hidden Nodes in Artificial Neural Network”, International Journal of Computer Science and Mobile Computing, Vol. 3, Issue.11, 455–464.
20. Butter, C. D., and Hocker, G. D.(1978), “ Fiber optics strain gauge”, Applied optics., 17, 2867–869.

21. *Lunia, A., Isaac, K. M., Chandra shekhara, K., and Watkins, S. E.(2000), "Aerodynamic testing of a smart composite wing using fiber-optic strain sensing and neural networks", Smart Material and Structure, 9, 767–773.*

22. *Haslach H. W Jr. and Sirkis J. S (1991), "Surface mounted optical fiber strain sensor design", Applied Optics, Optical Society of America, 30, No.28.*

23. *Hrabina J., Lazar J., Holá M., and Číp O., (2013)," Frequency Noise Properties of Lasers for Inter ferometry in Nanometrology", Sensors 13, 2206–2219.*

AUTHORS PROFILE

Ashwarya sheel wali, I completed bachelors of technology from Uttar Pradesh technical university in 2008 with first division. Thereafter I joined an engineering collage and taught as lecturer for three years. Then I got selected for M.tech at I.I.T(Madras). I completed my master's degree in technology in 2013 from department of applied mechanics in the area of self healing of polymer composites. Same year I joined I.I.T (B.H.U) for my Ph.D in department of mechanical engineering.

My area of research includes structural health monitoring using fiber optic sensors integrated with neural network analysis. I attended international conferences where I got my paper accepted for publication. I had got one publication accepted in international journal scopus indexed. At present I am working as senior research scholar at I.I.T (B.H.U).

Dr. Amit Tyagi is presently working as Associate professor in department of mechanical engineering at I.I.T(B.H.U). He had completed his bechalors degree in 1998 from G. B. Pant University of Agriculture and Tech. Pantnagar, Uttarakhand and his masters degree in 2001 from I.I.T Roorkee. He completed his Ph.D in mechanical engineering from I.I.T (B.H.U) in 2011. His area of interest includes vibration , sensors, structural health monitoring. He had also contributed in sponsored projects for BARC in year 2013-16.

He had publications in international journal starting from 2010 till this year. Moreover he had participated in many conferences and contributed in exchange of knowledge. He is an active member in department of mechanical engineering.